Title - *Democracy and Mobility: A preliminary analysis of global adherence to non-pharmaceutical interventions for COVID-19*

Authors - Cristina M. Herren PhD*[1, 2], Tenley K. Brownwright PhD*[3, 4], Erin Y. Liu MSc[5, 6], Nisrine El Amiri MPH[7,8], Maimuna S. Majumder PhD[9,10]

**These authors contributed equally to this work.*

Affiliations:

[1] Department of Biomedical Informatics, Harvard Medical School, Boston, MA, USA

[2] Harvard Data Science Initiative, Harvard University, Cambridge, MA, USA

[3] Center for Infectious Disease Dynamics, Pennsylvania State University, State College, PA, USA

[4] Department of Biology, Pennsylvania State University, State College, PA, USA

[5] Department of Epidemiology, Biostatistics and Occupational Health, McGill University, Montréal, QC, Canada

[6] McGill Clinical and Health Informatics, McGill University, Montréal, QC, Canada

[7] Child Health Evaluative Sciences Program, SickKids Hospital, Toronto, Canada

[8] Department of Obstetrics & Gynaecology, University of British Columbia, Vancouver, Canada

[9] Computational Health Informatics Program, Boston Children's Hospital, Boston, MA, USA

[10] Department of Pediatrics, Harvard Medical School, Boston, MA, USA

Corresponding Author:

Cristina M. Herren PhD

cristina_herren@hms.harvard.edu

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ABSTRACT: In the absence of vaccines or therapeutics, and with cases of COVID-19 continuing to grow each day, most countries are relying on non-pharmaceutical interventions (NPIs) to reduce the spread of SARS-CoV-2. The goal of NPIs – decreasing mobility in order to decrease contact – comes with competing socioeconomic costs and incentives that are not well-understood. Using Google's Community Mobility data, we visualized changes in mobility and explored the effect of economic, social, and governmental factors on mobility via regression. We found decreases in mobility for all movement categories except in residential areas; these changes corresponded strongly with country-specific outbreak trajectory. Mobility increased with GDP per capita, though this relationship varied among movement categories. Finally, countries with more authoritarian governments were more responsive with respect to mobility changes as local case counts increased; however, these countries were also less likely to report mobility data to Google. These preliminary findings suggest that country-specific outbreak trajectory, GDP per capita, and democracy index may be important indicators in assessing a given population's adherence to NPIs.

COMMENT:

With cases of COVID-19 increasing rapidly, no universally accepted treatment available, and vaccines many months away, most governments have implemented policies to curb transmission by reducing contact between individuals. These non-pharmaceutical interventions (NPIs) include closing schools, border closures, domestic movement restrictions, and lockdowns (targeted and nationwide).

Population compliance with NPIs has been observably heterogeneous and is likely dependent on sociodemographics.[1] Most NPIs – which disrupt mobility, and in turn commerce – impose economic burdens that may make such interventions difficult to sustain over prolonged periods of time.[2] Others have noted that these NPI-associated economic burdens are expected to vary across populations;[1,3] nevertheless, countries with weaker infrastructure may face larger consequences for delayed action.[4] Here, we attempt to disentangle some of the competing costs and incentives that make adherence to NPIs and resulting decreases in mobility difficult to predict across populations.

Using Google's recently-released Community Mobility data[5], we first visualized global changes in mobility as of March 29, 2020 (Figure 1). Because mobility data were only available for 130 of 198 countries, we conducted a multiple logistic regression to assess whether countries with reported data were meaningfully different from the remaining 68 (Appendix 2). Though there was no strong differentiation in GDP per capita or internet penetration across these two categories, we found that mobility data were more likely to be available for more democratic countries than for more authoritarian ones ($p = 0.011$) (Appendix 2). Notably, these data represent the subset of the population using a cell phone with location tracking enabled.

Proceeding with the countries for which mobility data were available, we observed that there were noticeable changes in movement when compared against baseline estimates as observed during a five week period from January to early February, 2020 (Figure 1). In an assumed response to the pandemic, all countries exhibited decreased movement in retail and transit (average change of -58.6% and -58.8%, respectively), most countries exhibited decreased movement in grocery/pharmacy (-37.7%), parks (-38.2%), and work (-33.4%), whereas movement in residential areas increased slightly (+16.3%).

To assess possible indicators for change in mobility among the countries for which mobility data were available, we implemented a multiple linear regression in which we predicted mobility scores as a function of movement category, trajectory of the outbreak within each country, and broader politico-economic indices for each country (Appendix 2).

We found that changes in mobility corresponded strongly with country-specific outbreak trajectory. Mobility decreased in response to both the number of total reported cases per capita ($p = 0.012$), as well as the number of new reported cases per capita ($p < 0.0001$). However, the relationship of mobility in response to new reported cases per capita indicated a strong interaction with democracy index; countries with more authoritarian governments experienced stronger reductions in movement in response to increases in new reported cases per capita ($p < 0.0001$). Nevertheless, it is worth noting that reporting of new cases may be confounded with democracy index, with more transparent case-reporting in more democratic countries.

We also observed a non-linear relationship between mobility and time-since-first-case was reported, with an initial decrease in mobility followed by an increase as time-since-first-case increased ($p = 0.0018$). In fact, time-since-lockdown and time-since-initial-social-distancing were both significant predictors ($p < 0.0001$ for both), but in opposite directions. Namely, when outbreak trajectory over time is taken into account, a greater time-since-lockdown was associated with lower mobility, whereas a greater time-since-initial-social-distancing was associated with higher mobility – indicating that social distancing may be insufficient on its own (i.e. in the absence of lockdown) to prompt sustained reductions in mobility.

Changes in mobility were strongly dependent upon the type of activity, as indicated by movement category ($p < 0.0001$). Additionally, mobility was higher as GDP per capita increased (Appendix 2). However, the relationship between GDP per capita and mobility varied by mobility category ($p = 0.017$), with especially strong increases in movement within parks and residential areas in higher-GDP countries.

These preliminary findings suggest that GDP per capita, country-specific outbreak trajectory, and democracy index may be important indicators in assessing a given population's adherence to NPIs. While we were limited by the use of a mobility data source that appears to differentially exclude less democratic countries, we believe that this is a finding in and of itself and – when combined with the results we obtained from countries for which mobility data were available – suggests that further investigation at the intersection of democracy and mobility is warranted within the context of the ongoing COVID-19 pandemic.

Figure Legends:

Figure 1. *Change in mobility from baseline reported by Google Community Mobility Reports on March 29, 2020*. Panels A-F correspond to retail, grocery/pharmacy, parks, transit, work, and residential movement categories.

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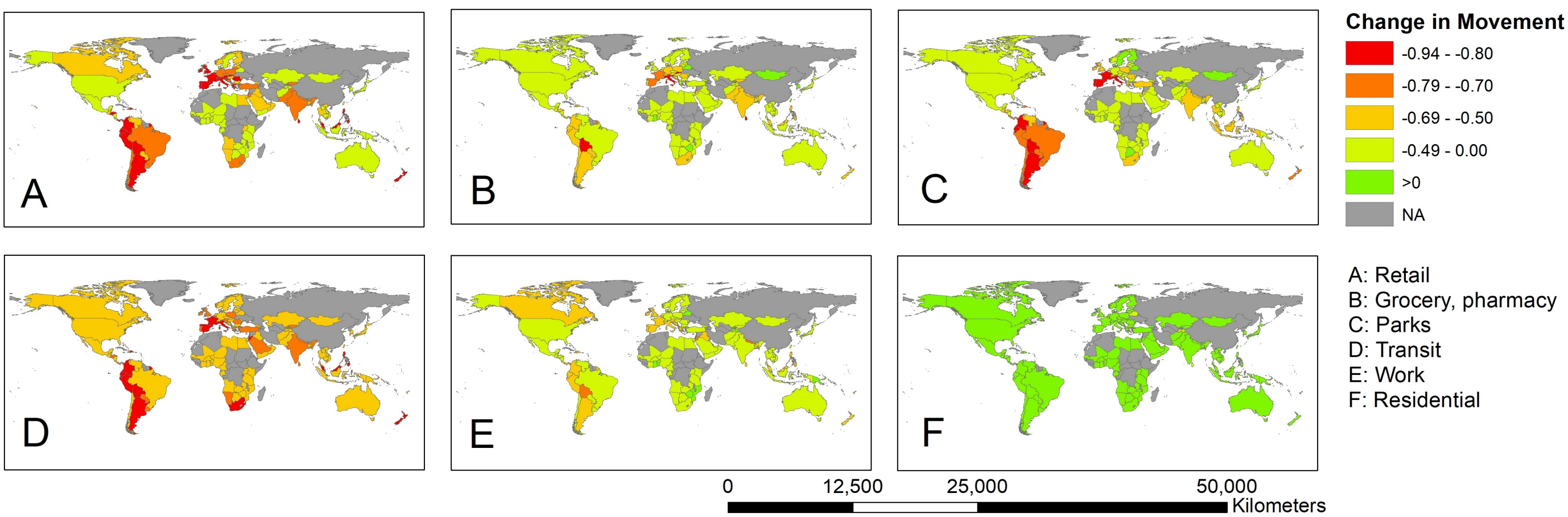
A
B
C
D
E
F
Change in Movement
-0.94 - -0.80
-0.79 - -0.70
-0.69 - -0.50
-0.49 - 0.00
>0
NA
A: Retail
B: Grocery, pharmacy
C: Parks
D: Transit
E: Work
F: Residential
0
12,500
25,000
50,000
Kilometers

APPENDIX 1: Data Sources and Curation

Data Column	Data Source	Data Entry Description	N (%) Values Missing	
Mobility values	Google Community Mobility Reports[1]	Manually entered values from PDFs provided by Google Mobility.	Retail and Recreation	68 (34.34)
			Grocery and Pharmacy	68 (34.34)
			Parks	69 (34.85)
			Transit stations	69 (34.85)
			Workplaces	68 (34.34)
			Residential	71 (35.86)
GDP	World Bank[2]	Downloaded and merged csv file. All GDP values are reported based on latest data available: 2018 or 2017, with exceptions: 1. South Sudan: 2015 2. Syria (Syrian Arab Republic): 2007 3. Venezuela (Bolivarian Republic of Venezuela): 2014 The following countries did not report GDP to WorldBank and data was obtained from alternate sources: 4. North Korea: 2016[3] 5. State of Palestine: 2017[4] 6. Taiwan: 2018[5]	4 (2.02)	
Population	Worldometer[6]	Matched countries with population data in R version 3.4.0 and manually filled the values for	0 (0.00)	

		remaining countries. Used this method for all data obtained from Worldometer.	
Democracy index	Economist Intelligence Unit[7]	Manually entered from PDF of White Paper.	32 (16.16)
NPI interventions	Assessment Capacities Project (ACAPS) COVID19 Government Measures Data[8]; Wikipedia[9]	Identified the first intervention for each country for both pre-defined intervention types. Calculated the number of days prior to 29 March 2020 that these interventions had been in place in R 3.4.0. No intervention in a given category was recorded as a 0 (every intervention had at least one day recorded). Obtained data for countries with no records from timelines of COVID-19 outbreaks on Wikipedia.	Time since lockdown 0 (0.00) Time since initial social distancing 0 (0.00)
Cases per million	Worldometer[10]	Used total cases reported on Worldometer (last archived version on 29 March 2020, obtained through archive.org) or "Yesterday" table (obtained on 05 April 2020). Note: "The "New" columns for China display the previous day changes (as China reports after the day is over). For all other countries, the "New" columns display the changes for the current day while still in progress.	0 (0.00)
New cases per million	Worldometer[10]	Used new cases reported on Worldometer site, found in last archived version on 29 March 2020 (obtained through archive.org). Note: Puerto Rico's COVID numbers came from Puerto Rico Department of Health website[11]	0 (0.00)

Time since first case	Worldometer[10]	Used date of first case reported on Worldometer site, from last archived version on 29 March 2020 (obtained through archive.org). Calculated number of days from first case to 29 March 2020 using R 3.4.0.	18 (9.09)
Internet users	Wikipedia[12]	Manually entered the proportion of population that are internet users.	3 (1.52)

All data were manually reviewed by coauthors. First, EYL spot-checked mobility values for ~ 10 random countries (no changes were necessary). Then, TKB and EYL did a complete check of all COVID-19 variables (cases per million, new cases per million, date of first case), and additional checks of socioeconomic values. EYL and TKB performed a spot-check of population and GDP and full, manual checks of all countries with non-identical matching names between datasets. EYL and TKB did a full, manual check of Democracy Index. CMH checked NPI data.

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APPENDIX 2: Mobility and Inclusion Analyses

Mobility analysis:

We used multiple regression analysis to evaluate the change in mobility as a function of several economic, political, and epidemiological variables for each country. We modeled each mobility value as a function of the movement category (Grocery/Pharmacy, Workplace, Residential, Parks, Retail/Recreation, and Transit), GDP per capita, democracy index, log-transformed number of new cases in the prior day (per million people), log-transformed number of total cases (per million people), number of days since the first case, a quadratic term for number of days since the first case, number of days since the first lockdown was implemented within a country, and number of days since the first social distancing policies were implemented within a country. We included an interaction between GDP per capita and movement category to allow the effect of GDP per capita to differ between movement categories. This interaction term corresponded to our hypothesis that wealthier (per capita) nations might see a shift in recreation or work that differed from the shifts in those categories for lower-GDP (per capita) nations. We also included an interaction between the log-transformed number of new cases and the democracy index, which allowed the effect of new cases to vary by the democratic leaning of a nation's government. This interaction corresponded to our hypothesis that mobility in nations with authoritarian governments might be more responsive to increasing local caseloads. When log-transforming the variables for new cases per million and total cases per million, we replaced zero values with one-tenth the minimum non-zero value. Replacing zeroes with one-fifth the minimum non-zero value yielded the same qualitative results in our analyses. We evaluated significance using a type III sums of squares anova on linear model fits, using the "car" package in R.

MODEL INFO: Main Text Mobility Analysis
Observations: 712 (63 missing obs. deleted)
Dependent Variable: Mobility Values
Type: OLS linear regression

MODEL FIT:
F(19,692) = 84.6087, p = 0.0000
$R^2 = 0.6991$
Adj. $R^2 = 0.6908$

Standard errors: OLS

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-4.36E-01	4.57E-02	-9.544	< 2e-16	***
log(Cases per million)	-1.73E-02	6.86E-03	-2.519	0.01198	*
Days since first case	-6.81E-03	2.09E-03	-3.263	0.00116	**
Days since first case^2	7.85E-05	2.51E-05	3.129	0.00183	**
Time-since-lockdown	-9.87E-03	1.11E-03	-8.907	< 2e-16	***
Time-since-social-distancing	5.11E-03	7.71E-04	6.621	7.18E-11	***
Grocery/Pharmacy	1.79E-01	3.08E-02	5.812	9.44E-09	***
Parks	1.63E-01	3.08E-02	5.305	1.52E-07	***
Transit	-5.09E-03	3.09E-02	-0.165	0.86915	
Workplace	2.59E-01	3.08E-02	8.417	< 2e-16	***
Residential	7.03E-01	3.09E-02	22.76	< 2e-16	***
GDP per capita	3.49E-07	8.87E-07	0.394	0.69404	
log(New cases per million)	-3.52E-02	7.28E-03	-4.831	1.68E-06	***
Democracy index	-8.73E-03	4.47E-03	-1.953	0.05117	.
Grocery/Pharmacy * GDP per capita	1.65E-06	1.11E-06	1.495	0.13528	
Parks * GDP per capita	2.73E-06	1.11E-06	2.471	0.01372	*
Transit * GDP per capita	4.06E-07	1.11E-06	0.367	0.71395	
Workplace * GDP per capita	-2.12E-07	1.11E-06	-0.191	0.84827	
Residential * GDP per capita	2.57E-06	1.11E-06	2.324	0.02041	*
log(New cases per million) * Democracy index	4.37E-03	1.10E-03	3.981	7.60E-05	***

Anova Table (Type III tests): Main Text Mobility Analysis

Response: Mobility Values

	Sum Sq	Df	F value	Pr(>F)	
(Intercept)	3.1048	1	91.0828	< 2.2e-16	***
log(Cases per million)	0.2164	1	6.3473	0.01198	*
Days since first case	0.363	1	10.6477	0.001156	**
Days since first case^2	0.3337	1	9.7896	0.001829	**
Time-since-lockdown	2.7046	1	79.3412	< 2.2e-16	***
Time-since-social-distancing	1.4942	1	43.8333	7.18E-11	***
Movement category	24.0949	5	141.3691	< 2.2e-16	***
GDP per capita	0.0053	1	0.1549	0.694044	
log(New cases per million)	0.7954	1	23.3346	1.68E-06	***
Democracy index	0.1301	1	3.8158	0.051174	.
Movement category * GDP per capita	0.4733	5	2.777	0.017088	*
log(New cases per million) * Democracy index	0.5401	1	15.8454	7.60E-05	***
Residuals	23.5888	692			

Sensitivity analyses for mobility analysis:

Robustness of Democracy Index x New Cases Interaction

To evaluate the robustness of the interaction between log-transformed new cases per million people and democracy index, we conducted another analysis where democracy index was converted to a binary variable, based on whether the democracy index was greater than 5 or less than 5. We repeated the above multiple regression analysis, using this binary variable in place of the democracy index. Results for this analysis were qualitatively similar to the original analysis, with a significant interaction between the binary democracy predictor and log-transformed new cases per million people.

MODEL INFO: Mobility Analysis With Binary Democracy Variable
Observations: 742 (33 missing obs. deleted)
Dependent Variable: Mobility Values
Type: OLS linear regression

MODEL FIT:
$F(19,722) = 86.7589$, $p = 0.0000$
$R^2 = 0.6954$
Adj. $R^2 = 0.6874$

Standard errors: OLS

	Estimate	Std. Error	t value	Pr(>|t|)	p
(Intercept)	-5.09E-01	3.75E-02	-13.567	< 2e-16	***
log(Cases per million)	-3.24E-02	6.20E-03	-5.227	2.26E-07	***
Days since first case	-2.86E-03	1.96E-03	-1.463	0.143769	
Days since first case^2	3.45E-05	2.37E-05	1.454	0.146335	
Time-since-lockdown	-9.10E-03	1.11E-03	-8.204	1.07E-15	***
Time-since-social-distancing	4.91E-03	7.60E-04	6.457	1.97E-10	***
Grocery/Pharmacy	1.79E-01	3.06E-02	5.854	7.28E-09	***
Parks	1.62E-01	3.06E-02	5.285	1.66E-07	***
Transit	-9.87E-03	3.07E-02	-0.321	0.748051	
Workplace	2.55E-01	3.06E-02	8.319	4.42E-16	***
Residential	7.04E-01	3.07E-02	22.932	< 2e-16	***
GDP per capita	8.39E-07	8.65E-07	0.97	0.332535	
log(New cases per million)	-1.68E-02	4.18E-03	-4.023	6.34E-05	***
Binary democracy variable	-4.48E-03	1.61E-02	-0.278	0.781094	
Grocery/Pharmacy * GDP per capita	1.69E-06	1.11E-06	1.522	0.128489	
Parks * GDP per capita	2.68E-06	1.11E-06	2.416	0.015956	*
Transit * GDP per capita	3.92E-07	1.11E-06	0.353	0.724393	
Workplace * GDP per capita	-2.34E-07	1.11E-06	-0.211	0.83286	
Residential * GDP per capita	2.65E-06	1.11E-06	2.386	0.017295	*
log(New cases per million) * Binary democracy variable	1.52E-02	4.58E-03	3.311	0.000977	***

Robustness of Social Distancing Coefficient

Within the distribution of times since social distancing policies were enacted, there were a small number of countries that had implemented social distancing for long periods of time (upwards of 40 days). These countries were generally geographically close to China and often had local outbreaks sooner than other countries. We were concerned that this small cluster of countries might bias the coefficient for time since social distancing. Thus, we removed all countries with a time since social distancing policies of greater than 40 days and repeated the multiple regression analysis. The coefficient for time since social distancing remained positive and strongly significant, indicating little bias from these countries.

MODEL INFO: Mobility Analysis Without Countries With Prolonged Social Distancing

Observations: 694 (63 missing obs. deleted)

Dependent Variable: Mobility Values for Countries With Fewer than 40 Days S

Type: OLS linear regression

MODEL FIT:

$F(18,675) = 87.1923$, $p = 0.0000$

$R^2 = 0.6993$

Adj. $R^2 = 0.6912$

Standard errors: OLS

	Estimate	Std. Error	t value	Pr(>|t|)	p
(Intercept)	-4.18E-01	4.88E-02	-8.559	< 2e-16	***
log(Cases per million)	-1.74E-02	6.85E-03	-2.541	1.13E-02	*
Days since first case	-7.22E-03	2.09E-03	-3.449	5.98E-04	***
Days since first case^2	8.52E-05	2.53E-05	3.369	7.98E-04	***
Time-since-lockdown	-9.92E-03	1.17E-03	-8.453	< 2e-16	***
Time-since-social-distancing	4.63E-03	1.22E-03	3.795	0.000161	***
Grocery/Pharmacy	1.79E-01	3.09E-02	5.783	1.12E-08	***
Parks	1.62E-01	3.09E-02	5.228	2.29E-07	***
Transit	-5.02E-03	3.10E-02	-0.162	0.87152	
Workplace	2.61E-01	3.09E-02	8.441	< 2e-16	***
Residential	7.11E-01	3.10E-02	22.923	< 2e-16	***
GDP per capita	3.83E-07	9.01E-07	0.426	0.670598	
log(New cases per million)	-3.35E-02	7.35E-03	-4.565	5.95E-06	***
Democracy index	-1.05E-02	4.62E-03	-2.268	0.023632	*
Grocery/Pharmacy * GDP per capita	1.73E-06	1.12E-06	1.535	0.125363	
Parks * GDP per capita	2.88E-06	1.12E-06	2.563	0.010586	*
Transit * GDP per capita	5.48E-07	1.13E-06	0.486	0.626928	
Workplace * GDP per capita	-1.18E-07	1.12E-06	-0.105	0.916154	
Residential * GDP per capita	2.90E-06	1.13E-06	2.571	0.010349	*
log(New cases per million) * Democracy index	4.26E-03	1.10E-03	3.887	0.000112	***

Aggregate Effect of GDP Per Capita

Because of the interaction term between GDP per capita and movement category, our original model did not estimate an overarching effect of GDP on mobility scores (rather, it provided six estimates of the effect of GDP on mobility scores, with one for each movement category). To evaluate the overall trend between mobility scores and GDP per capita, we removed the interaction term and re-ran the model. We found a strong positive association between GDP per capita and overall mobility.

MODEL INFO: Mobility Analysis Without GDP Interaction
Observations: 712 (63 missing obs. deleted)
Dependent Variable: Mobility Values
Type: OLS linear regression

MODEL FIT:
$F(14,697) = 112.4014$, $p = 0.0000$
$R^2 = 0.6930$
Adj. $R^2 = 0.6869$

Standard errors: OLS

	Estimate	Std. Error	t value	Pr(>|t|)	p
(Intercept)	-4.57E-01	4.43E-02	-10.322	< 2e-16	***
log(Cases per million)	-1.73E-02	6.91E-03	-2.5	0.01265	*
Days since first case	-6.82E-03	2.10E-03	-3.247	0.00122	**
Days since first case^2	7.86E-05	2.53E-05	3.113	0.00192	**
Time-since-lockdown	-9.87E-03	1.12E-03	-8.853	< 2e-16	***
Time-since-social-distancing	5.11E-03	7.76E-04	6.58	9.26E-11	***
Grocery/Pharmacy	2.08E-01	2.41E-02	8.624	< 2e-16	***
Parks	2.11E-01	2.41E-02	8.76	< 2e-16	***
Transit	1.90E-03	2.41E-02	0.079	0.93724	
Workplace	2.55E-01	2.41E-02	10.599	< 2e-16	***
Residential	7.48E-01	2.41E-02	30.983	< 2e-16	***
GDP per capita	1.54E-06	5.30E-07	2.908	0.00375	**
log(New cases per million)	-3.52E-02	7.33E-03	-4.806	1.89E-06	***
Democracy index	-8.74E-03	4.50E-03	-1.944	0.05235	.
log(New cases per million) * Democracy index	4.37E-03	1.10E-03	3.96	8.25E-05	***

Inclusion analysis:

The large number of missing data for mobility values has the potential to bias the results of our analyses. We evaluated which factors are associated with missingness of mobility data to ascertain how this might impact the interpretation of our mobility analyses.

For each country, we generated a binary variable corresponding to whether there was at least 1 mobility value reported by Google. We used a logistic regression to evaluate which of the following predictors were related to a higher probability of inclusion within the mobility dataset: fraction of the population that are internet users, democracy index, and GDP per capita. When using type III sums of squares, only the democracy index was a significant predictor of inclusion in the dataset, with more democratic countries having a higher probability of inclusion.

MODEL INFO: Logistic Regression Predicting Mobility Data Reporting
Observations: 164 (34 missing obs. deleted)
Dependent Variable: Reported or Unreported
Type: Generalized linear model
Family: binomial
Link function: logit

MODEL FIT:
$\chi^2(3) = 20.7884$ $p = 0.0001$
Pseudo-R^2 (Cragg-Uhler) = 0.1742
Pseudo-R^2 (McFadden) = 0.1102
AIC = 175.9233 BIC = 188.3227

Standard errors: MLE

	Estimate	Std. Error	z value	Pr(>|z|)	
Intercept	-8.35E-01	5.47E-01	-1.528	0.1265	
GDP Per Capita	1.76E-05	2.15E-05	0.817	0.4139	
Democracy Index	2.75E-01	1.08E-01	2.557	0.0106	*
Internet Users	6.14E-01	9.81E-01	0.626	0.5312	